**Measuring power outage exposure using a novel national dataset of power outages, 2018-2020**

**Introduction:**

Power outage incidence is increasing[[1]](#endnote-1),[[2]](#endnote-2). Climate change has increased the frequency and intensity of severe weather, the most common cause of power outages[[3]](#endnote-3),[[4]](#endnote-4),[[5]](#endnote-5). At the same time, the United States electrical grid is aging[[6]](#endnote-6),[[7]](#endnote-7). Grid components have not been modernized to withstand the previously rare extreme heat, wind, and precipitation now commonplace with climate change[[8]](#endnote-8). As a result, US electrical customers experienced an average of 8 hours without power in 2020, the longest duration on record[[9]](#endnote-9).

Power outages pose serious health risks to vulnerable people. For those who use life-sustaining electricity-dependent medical equipment such as at-home ventilators and oxygen tanks, loss of electricity can be life-threatening[[10]](#endnote-10). In children, outages increase accidents and injuries related to generator and natural gas use[[11]](#endnote-11). Power outages render air conditioners, heaters, and tap water unavailable. This can cause heat exposure, cold exposure, and dehydration in affected populations. Older adults are susceptible to health effects from these extreme temperature exposures and dehydration, which can lead to stoke, myocardial infarction, and other adverse cardiorespiratory outcomes[[12]](#endnote-12),[[13]](#endnote-13),[[14]](#endnote-14),[[15]](#endnote-15). Outages also increase pediatric asthma emergencies from heat and humidity exposure absent air conditioning[[16]](#endnote-16).

Despite the health risks of power outage, especially to vulnerable populations, data describing power outage exposure is extremely limited[[17]](#endnote-17),[[18]](#endnote-18). This has constrained research on this exposure. Only one New York State-wide dataset describes outage exposure across space and time[[19]](#endnote-19), and most studies of power outage rely on this single dataset. The remaining studies use large-scale events such as hurricanes or disasters as a surrogate for power outage exposure[[20]](#endnote-20),[[21]](#endnote-21). These studies consider everyone in a city or county exposed to the large-scale event as exposed to power outage, in days or weeks following the event. Studies based on single events cannot disentangle the health effects of power outage exposure from disaster exposure, and cannot estimate exposure-response relationships between power outage exposure and health outcomes. Quantifying the risks of power outage exposure is essential to prevent CVD events, accidents and asthma in children, and other cardiorespiratory outcomes.

In our previous work, we created a new national dataset of hourly power outage exposure for all counties in the continental United States[[22]](#endnote-22). We used this dataset to describe power outage exposure by region and social vulnerability, finding that outages were more common in the southeast and northeast US, with high outage incidence and high social vulnerability co-occurring most frequently in the southeastern US. This dataset will allow us to characterize exposure-response relationships between power outage and health outcomes nationally, by region, and within vulnerable populations.

However, even with these new data, major challenges with power outage exposure assessment remain. First, there is no standard or widely used strategy to measure power outage exposure in the literature[[23]](#endnote-23). A single strategy to describe power outage exposure would allow comparability and aggregation of results across studies. Second, any definition of outage exposure will need to include a duration. on the health-relevant duration of a power outage: the duration at which an outage begins to cause health effects. There is no literature on the health-relevant duration of power outage with respect to any outcome. Incorrect assumptions about the health-relevant duration have the potential to bias the results of an epidemiological study of power outage and a health outcome. Finally, both the new national dataset and existing New York State data are missing large percentages of observations[[24]](#endnote-24),[[25]](#endnote-25). This missingness could also substantially bias results of an epidemiological study of power outage and any health outcome.

In this paper we will address these exposure measurement issues by developing a strategy for measuring power outage exposure. Then, we will run simulations to test how assumptions about health relevant duration of outage and missingness could bias the results of an epidemiological study of the health effects of power outage. Our results will allow us and other researchers to consistently define and measure power outage exposure using the datasets currently available, while minimizing potential bias in future epidemiological studies of power outages and health outcomes.

**Methods:**

**National PowerOutages.us dataset structure**

In our previous work, we created a national dataset of power outage exposure[[26]](#endnote-26). We purchased raw power outage data from PowerOutages.us. Most utility websites show the number of customers without power by neighbourhood or city in real time. To create this dataset, poweroutages.us scraped counts of customers without power from utility website APIs covering the continental US, in real time, every ten minutes from 2018-2020[[27]](#endnote-27).

The resulting dataset contains hourly counts of customers without power for each continental US county 2018-2020. Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business[[28]](#endnote-28). The counts of customers out do not necessarily track the same customers: if 10 people are reported without power in two subsequent hours in one county, the data do not contain information about whether the same 10 households were out. The data only show that 10 households were out in each hour.

The New York State power outage dataset is structured similarly – counts of customers without power are reported by hour by power operating divisions. Power operating divisions are a geographic unit varying in size throughout the state.

**Strategy to measure power outage**

To measure daily binary power outage exposure in the PowerOutages.us dataset and New York State dataset, we propose the following strategy. This strategy could be implemented in either the New York State data or PowerOutages.us data, but here we use the PowerOutages.us dataset as an example.

Since the health-relevant duration of power outage may change depending on the health outcome being examined in an epidemiological study, we suggest a definition of power outage exposure which is flexible to identify power outages of varying lengths. Although continuous measures of power outage are possible, we chose to measure daily binary exposure because binary metrics are easily interpretable by policy makers and non-scientists.

The measurement strategy we propose here is similar to previous definitions of power outage exposure used in the literature. To determine if a county-day was exposed to power outage, first we considered each hour of the day. We considered a county-hour exposed to power outage if the percentage of customers without power in county *i* during hour *j* exceeded an arbitrary cut point – for example, 10% of the customers. If more than 10% of customers served in county *i* were without power in hour *j*, there was a power outage in county *i* for hour *j*.

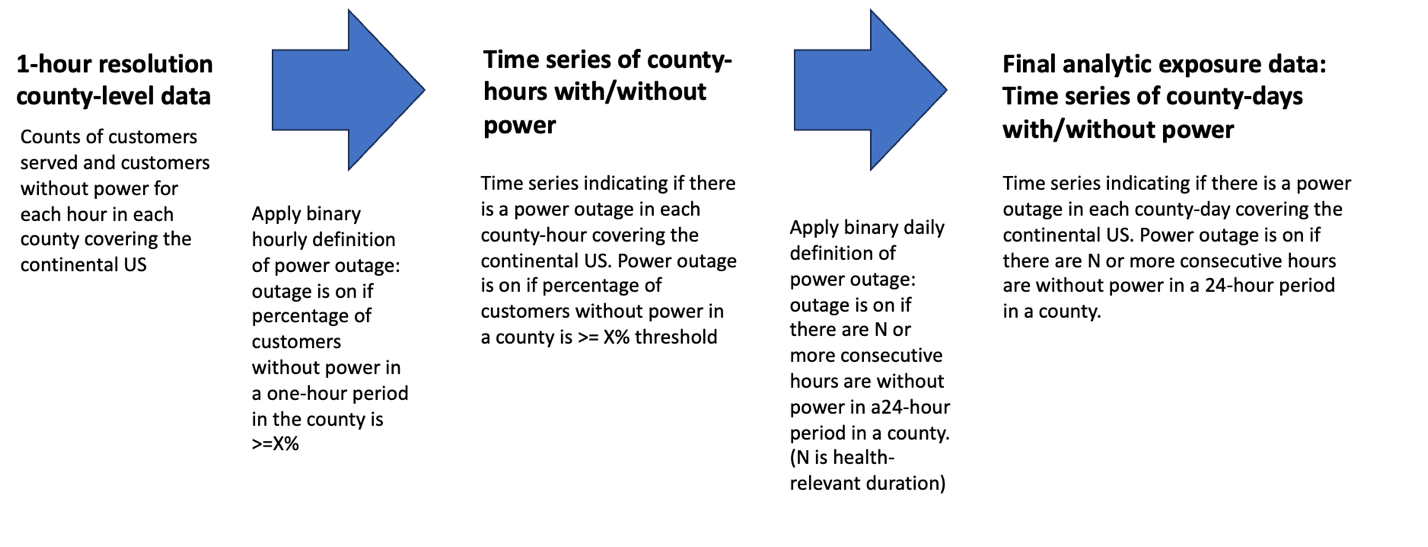
We then summarized this hourly exposure to the daily level: we chose a health-relevant duration (for example, 8 hours); this could be any duration chosen by a researcher. We considered a county-day as exposed if there were at least 8 consecutive hours of ‘power outage on’ (customers without power percentages > 10% of county) in that county on that day. Power outages could last more than 24 hours. We also considered a county-day as exposed if a power outage lasting longer than the health-relevant duration ended on that county-day.

Because a utility customer is a grid connection, meaning that one customer could be an apartment building or house where many people are living, and because counts of customers out do not necessarily track the same customers over time (if 10 people are reported without power in two subsequent hours in one county, the data do not contain information about whether the same 10 households were out - the data only show that 10 households were out in each hour), choosing a health relevant duration of 8 hours does not mean that there will always be 10% of people in the county experiencing an 8+ hour power outage. It does mean that many individuals were likely without power for close to 8 hours in the county. This is an areal unit measure: it doesn’t indicate what individuals were exposed to.

Relatedly, there is exposure misclassification inherent in this definition: when the county is ‘exposed’, some customers in the county will be without electricity and others will still have electricity. Other studies of power outage exposure using a similar exposure definition have dealt with this exposure misclassification by conducting sensitivity analyses varying the cut point after which a unit is considered exposed to power outage. For example, Northrop et al. considered a spatial unit exposed to power outage if more than 10% of the customers served in that unit were without power, and conducted two sensitivity analyses where they considered a spatial unit exposed to power outage if more than 20% and 30% of the customers served in that unit were without power[[29]](#endnote-29). As the cut point percentage increases, the specificity of this definition of power outage increases.

We propose using this strategy for measuring power outage exposure, and always conducting a sensitivity analysis on the cut point. This definition of power outage exposure allows us to specify a health-relevant duration of power outage for the health outcome of interest. It allows us to compare spatial units with different populations of customers served. It is also readily interpretable by policy makers. Exposure misclassification is inherent in a daily binary definition of power outage exposure, and this exposure measurement strategy allows us to conduct a sensitivity analysis by varying the cut-point used.

Here's a draft of a flowchart that might help keep this on the rails in the future?



**Bias from misidentifying health-relevant length and missing data**

This definition of power outage exposure allows us to specify a power outage duration of interest. For some exposures and outcomes, there may be threshold effects where power outages longer than a certain duration cause adverse health outcomes, but outages shorter than this duration do not. For example, back-up batteries for many life-sustaining electricity dependent medical devices last 8 hours. It may be that 8+ hour power outages affect the health of those using oxygen tanks and at-home ventilators, because after 8 hours of power outage, the batteries in these devices die, but shorter outages are covered by the battery. However, there is no literature describing how long power outages must be to cause health effects, with respect to any health outcome. Incorrect assumptions about the health-relevant duration have the potential to bias the results of an epidemiological study of power outage and a health outcome. Here, we attempt to quantify the magnitude and direction of bias introduced when researchers make incorrect assumptions about the health relevant length of outage.

Additionally, both the New York State dataset and PowerOutages.us dataset are missing large percentages of observations – some spatial units are missing up to 70% of observations. Including counties with substantial amounts of missing data in an analysis could introduce bias.

Missingness in the poweroutages.us dataset happens either because data are missing for an entire utility, because that utility did not have a website or it couldn’t be scraped. Data may also be missing because utility websites may be offline or inaccessible for long periods of time (months or years). In both cases, interpolating missing values is also near impossible because there is no data or very little existing data to extrapolate from.

To reduce bias due to missing data in an epidemiological study of power outage exposure and a health outcome using the poweroutages.us dataset, researchers could exclude counties that are missing more than a percentage of observations. Excluding counties with high missingness could result in less biased overall effect estimates. To do this, researchers must identify the threshold at which missing data in a county begins to severely bias effect estimates, and use this threshold to determine which counties to exclude from an analysis. In this simulation, we aimed to find this threshold.

**Simulations to test bias due to misidentifying health-relevant length of power outage and missing data**

We designed a simulation representing an epidemiological study measuring the association between power outage exposure and hospitalization rates by county-day for 1 year in 100 US counties. This outcome of ‘hospitalizations’ is intentionally vague, and could be any health outcome hypothesized to be caused by power outages. We simulated daily binary power outage exposure in the 100 US counties for 1 year, and daily county-level hospitalization over 1 year, and then generated effect estimates of power outage on hospitalization rates from this simulated data. We used this setup to test how much incorrect assumptions about the length of clinically relevant power outage, and missing data, would bias the results of an epidemiological study of power outage and a health outcome, like the one we simulated.

To set up these simulations, we generated 1 year of county-hour power outage exposure data for 100 simulated counties, by drawing counts of customers served in each county and hourly customers without power from the empirical distributions of customers served and without power in the PowerOutages.us dataset. We chose a health-relevant duration of power outage, 8+ hours. This was arbitrary – in a real study, the health-relevant duration would depend on the actual outcome being studied, and how power outages were thought to cause that outcome. We applied our above definition of power outage exposure to the 1 year of simulated counts of customers without power in each of the 100 simulated counties in the study. Using this definition, we identified county-days exposed to 8+ hour power outage.

We then generated outcome data based on this exposure data. For each of the 100 simulated counties, we drew hospitalization counts for each county-day based on the total number of customers served in a county from a Poisson distribution with a base rate of 0.1%. County-days that were exposed to 8+ hour outage received a 1% rate increase (for a total hospitalization rate of 0.101%). This produced one-year time series of daily hospitalization rates for each of the 100 counties.

To model a base case/unbiased scenario and estimate the true simulated effect of county-level 8+ power outage exposure on county-level hospitalization counts, we implemented a case-crossover design using a conditional Poisson model. Within each county, we chose control days for each day with non-zero hospitalization count, and included case and control days from all 100 in a Poisson model relating power outage exposure to hospitalization rates, with a fixed effect for county. We repeated this simulation, including exposure data creation, outcome data creation, and modelling, 100 times.

**Testing wrong assumptions about health relevant duration:**

To model exposure misclassification due to incorrect assumptions about the clinically relevant length of power outage, we first created two additional exposure datasets for each of the 100 counties, marking a county-day as exposed to power outage if there was either a 4+ hour outage, or 12+ hour outage on those days (customers without power counts > 10% of total customers for 4+ or 12+ consecutive hours), instead of an 8+ hour outages. We generated two additional datasets of outcome data for each of the 100 counties (simulated all-cause hospitalization data) based on the same hospitalization rate of 0.1%, and a 1% rate increase on days with 4+ hour and 12+ hour power outages, instead of 8+ hour outages.

We created a scenario meant to represent a researcher making wrong assumptions about the health-relevant duration of power outage. In this scenario, the true health relevant duration of power outage, causing increased hospitalizations, was 4+ or 12+, but the researcher had assumed 8+ power outages were relevant and identified these in the data. To represent this case, we paired exposure data indicating when counties were exposed to 8+ hour power outages with outcome data generated based on 4+ and 12+ hour exposure data, where days exposed to either 4+ or 12+ power outages had a 1% higher hospitalization rate.

We implemented the same study design as above to generate effect estimates: a case-crossover design using conditional Poisson models. For each county and scenario (8+ hour exposure data paired with outcome data generated based on 4+ outages, and 8+ hour exposure data paired with outcome data based on 12+ hour power outages) we chose control days for each day with non-zero hospitalization count. We used data from the 100 counties in two separate Poisson models to get effect estimates for each of the two mismatched scenarios.

We repeated these two simulation 100 times.

We also repeated the simulation an additional 100 times using a difference-in-differences design to test if results were sensitive to study design. Here, for each day exposed to power outage, we chose a control day not exposed to power outage from another county. We used those case and control days in a Poisson model to generate effect estimates for each of the two mismatched scenarios.

We calculated bias in the 4+ and 12+ hour cases using the absolute difference between the estimated effects and simulated effects (*𝛽*ˆ−*𝛽*; *𝛽*ˆ is the estimated effect and *𝛽* is the simulated effect) in each of the 100 models for each case using the case-crossover study design (Figure 1). We also calculated bias the same way for each of the 100 difference-in-differences models.

**Testing bias from missing data:**

To test bias from missing exposure data, we created four additional exposure datasets for each of the 100 simulated counties, each with an increasing percentage of missing observations (10%, 30%, 50%, 70%). To create missingness, we randomly removed county-hour observations from the original dataset until the correct percentage of observations were missing. We treated missing observations as though they indicated no power outage exposure (0 customers without power), since this is the average value of customers without power by hour in the poweroutages.us dataset, and it would be impossible to interpolate values more accurately in cases of actual missingness. We applied our definition of power outage exposure to these datasets containing missingness to create daily binary power outage exposure data for 1 year for the 100 counties based on a power outage duration of 8+ hours.

We then modeled the relationship between 8+ hour power outage exposure measured in each of the four datasets with missing data (10% - 70% missing data) and all-cause hospitalization counts generated based on a 8+ hour power outage exposure in the complete dataset with no missingness in the 100 counties. We used the case-crossover study design as above and a difference-in-differences design as above. We repeated the simulations 100 times.

We calculated bias in each of the four cases with increasing missingness again using the absolute difference between the estimated effects and simulated effects (*𝛽*ˆ−*𝛽*; *𝛽*ˆ is the estimated effect and *𝛽* is the simulated effect) in each of the 100 models for each case using the case-crossover study design and difference-in-differences design (Figure 1).

**Results:**

**Discussion:**

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